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Park

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(54) **SYSTEMS AND METHODS FOR CLASSIFYING DATA IN BUILDING AUTOMATION SYSTEMS**

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CPC ***G05B 15/02*** (2013.01); *G05B 2219/21088* (2013.01); *G05B 2219/25011* (2013.01)

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USPC 700/50; 707/769, 741; 709/206
See application file for complete search history.

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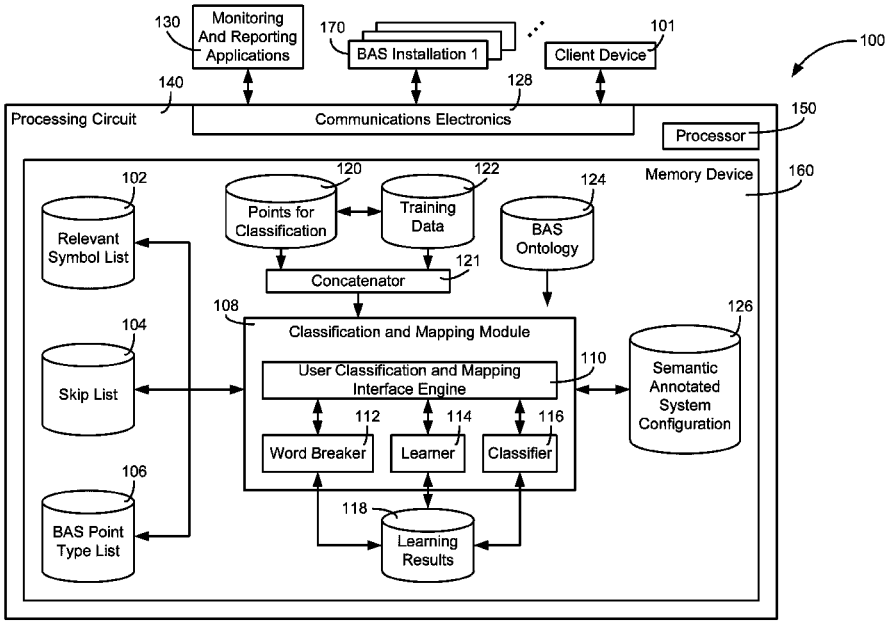
(57) **ABSTRACT**

A computerized method of assigning a building automation system point type to a plurality of unclassified data points is provided. The method includes receiving unclassified data points and attributes for each data point. The method includes receiving classifications for a first subset of the unclassified data points. Each classification associates a data point with a building automation system point type. The method includes generating a term set containing substrings that appear in the attributes. The method includes generating a first matrix describing a frequency that the substrings appear in the attributes. The method includes calculating an indicator of a probability that the presence of the selected substring results in the data point belonging to the selected point type. The method includes assigning a point type to a second subset by finding the substring and potential point type pair having the greatest indication of probability.

20 Claims, 5 Drawing Sheets



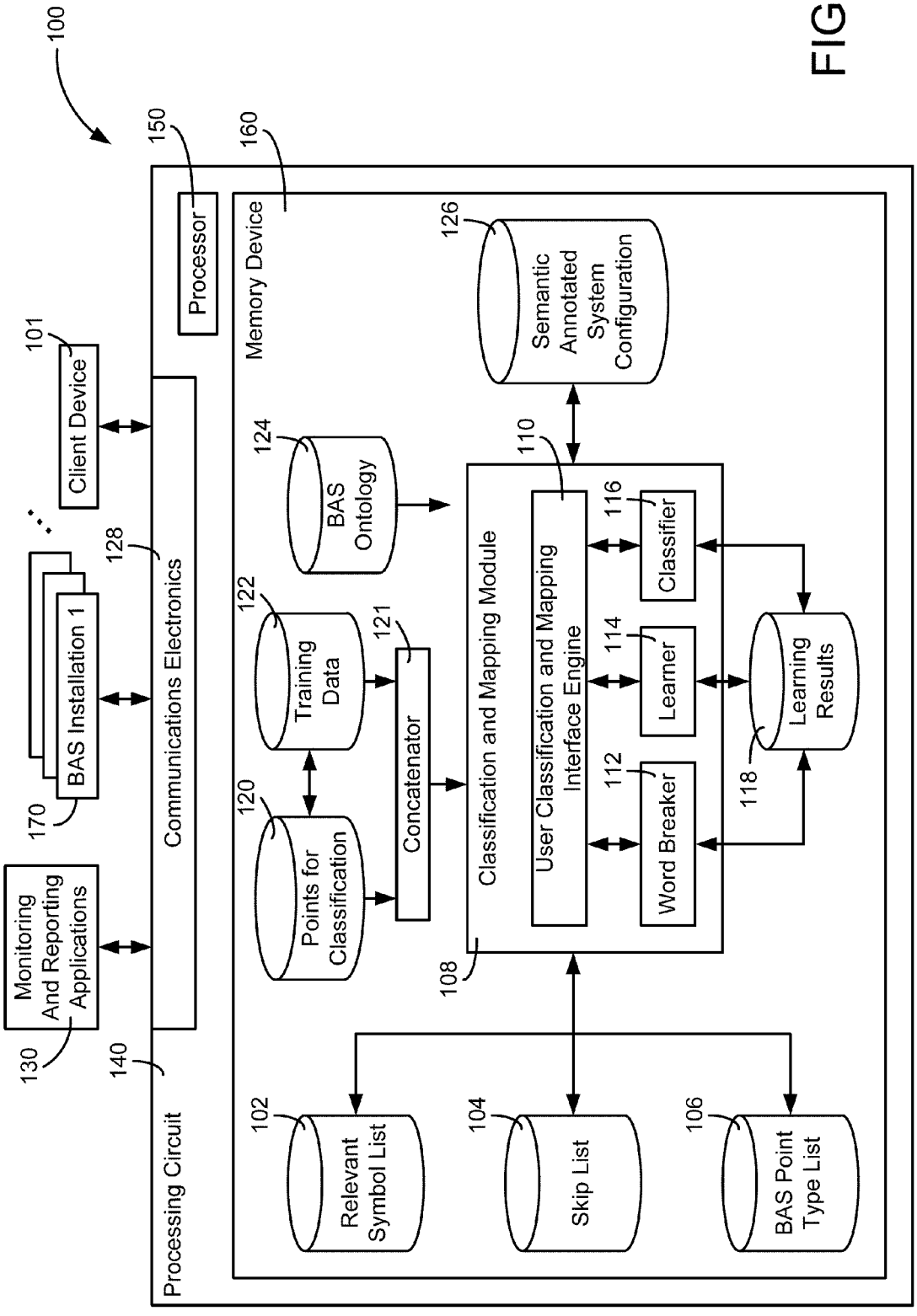

100
150
160
Processor
Memory Device
Client Device
101
126
Semantic Annotated System Configuration
124
BAS Ontology
110
116
Classifier
128
Communications Electronics
122
Training Data
121
Concatenator
Classification and Mapping Module
User Classification and Mapping Interface Engine
114
Learner
BAS Installation 1
170
120
Points for Classification
112
Word Breaker
118
Learning Results
Monitoring And Reporting Applications
130
140
108
Processing Circuit
102
Relevant Symbol List
104
Skip List
106
BAS Point Type List

FIG. 1

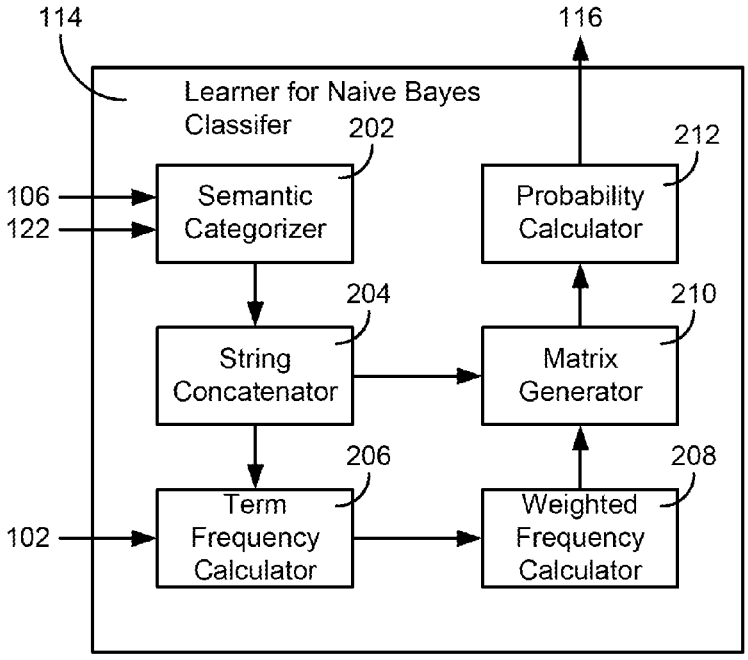

114
116
Learner for Naive Bayes Classifer
202
212
106
122
Semantic Categorizer
Probability Calculator
204
210
String Concatenator
Matrix Generator
206
208
102
Term Frequency Calculator
Weighted Frequency Calculator

FIG. 2A

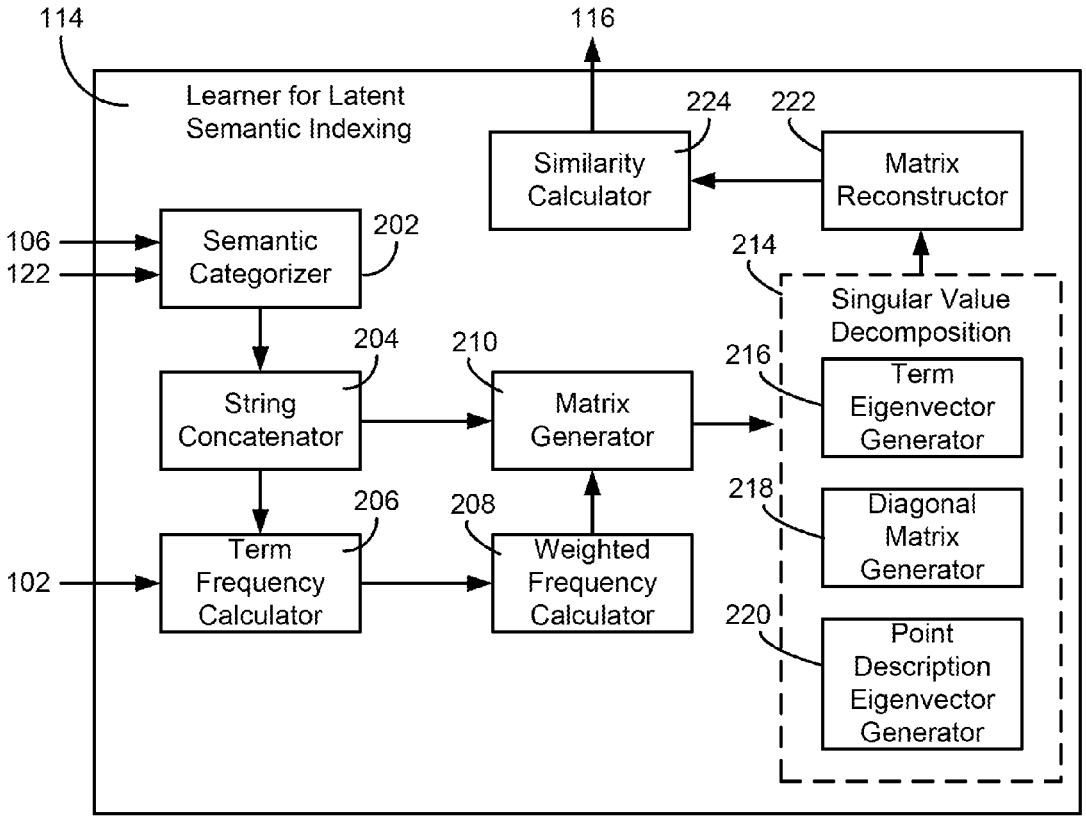

114
116
Learner for Latent Semantic Indexing
224
222
Similarity Calculator
Matrix Reconstructor
106
122
Semantic Categorizer
202
214
Singular Value Decomposition
204
210
216
String Concatenator
Matrix Generator
Term Eigenvector Generator
218
Diagonal Matrix Generator
206
208
102
Term Frequency Calculator
Weighted Frequency Calculator
220
Point Description Eigenvector Generator

FIG. 2B

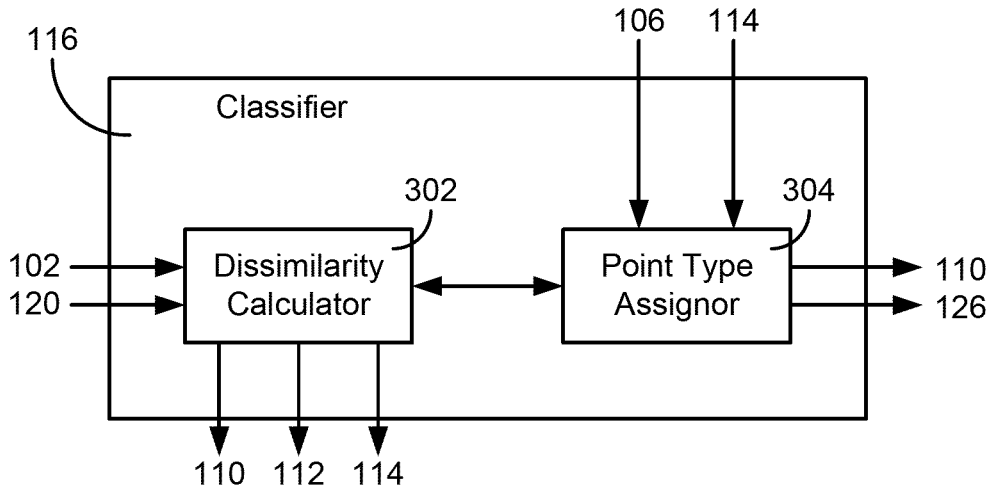

116
Classifier
106
114
302
304
102
120
Dissimilarity Calculator
Point Type Assignor
110
126
110
112
114

FIG. 3

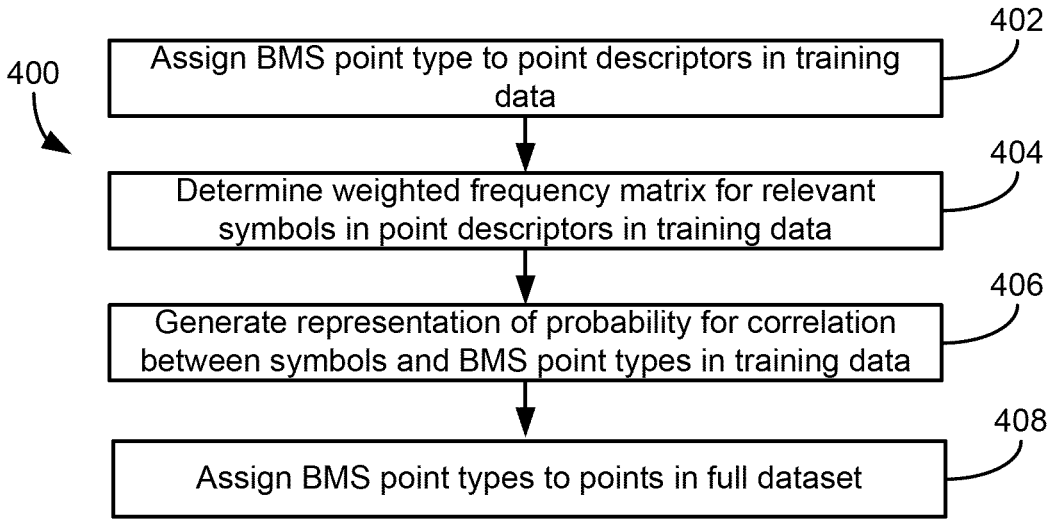

400
Assign BMS point type to point descriptors in training data
402
Determine weighted frequency matrix for relevant symbols in point descriptors in training data
404
Generate representation of probability for correlation between symbols and BMS point types in training data
406
Assign BMS point types to points in full dataset
408

FIG. 4

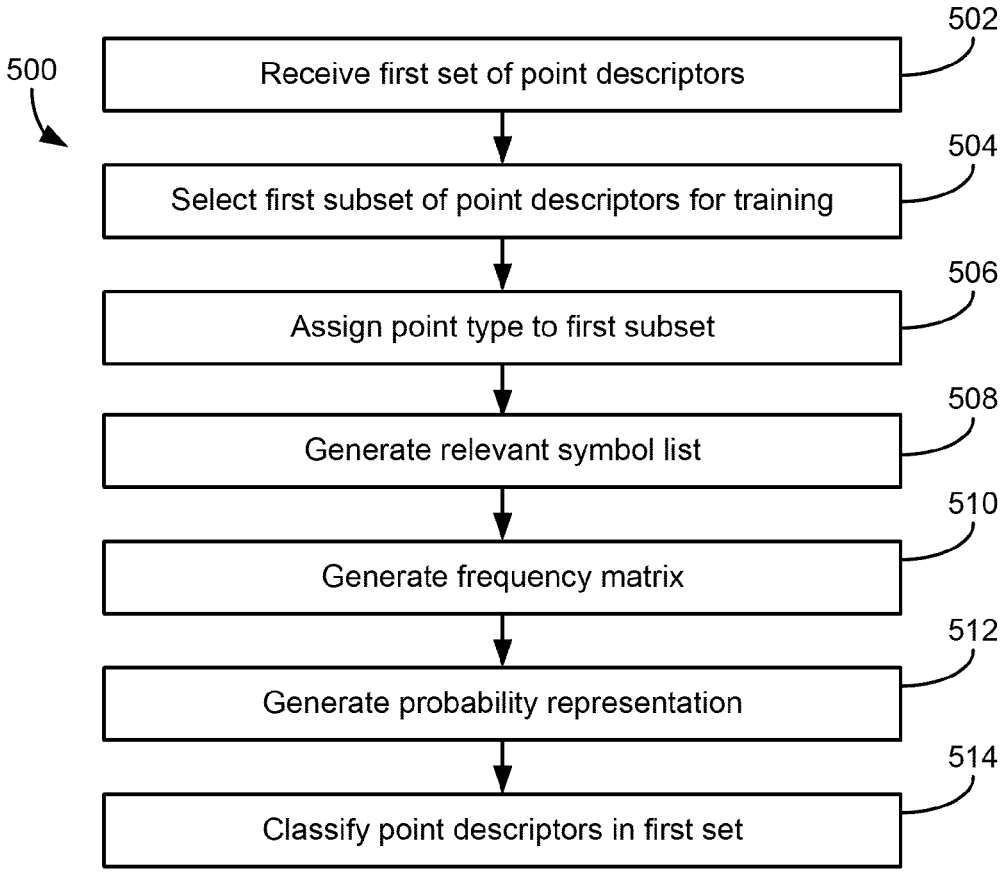

500
Receive first set of point descriptors
502
Select first subset of point descriptors for training
504
Assign point type to first subset
506
Generate relevant symbol list
508
Generate frequency matrix
510
Generate probability representation
512
Classify point descriptors in first set
514

FIG. 5

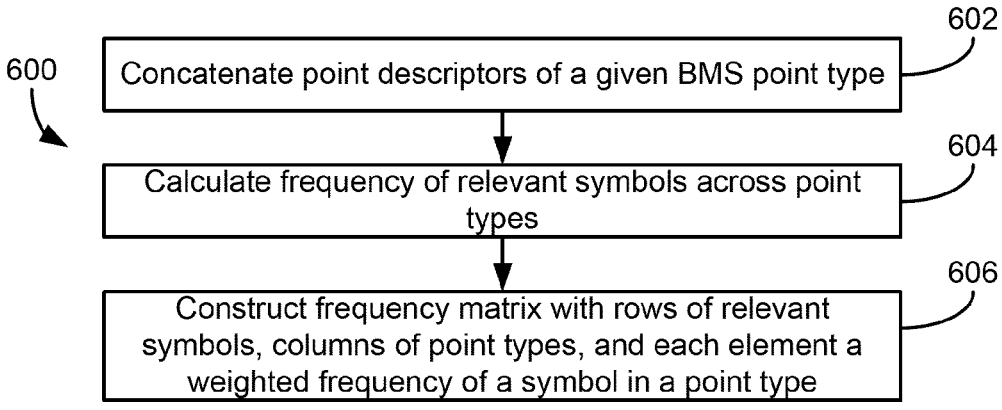

600
Concatenate point descriptors of a given BMS point type
602
Calculate frequency of relevant symbols across point types
604
Construct frequency matrix with rows of relevant symbols, columns of point types, and each element a weighted frequency of a symbol in a point type
606

FIG. 6

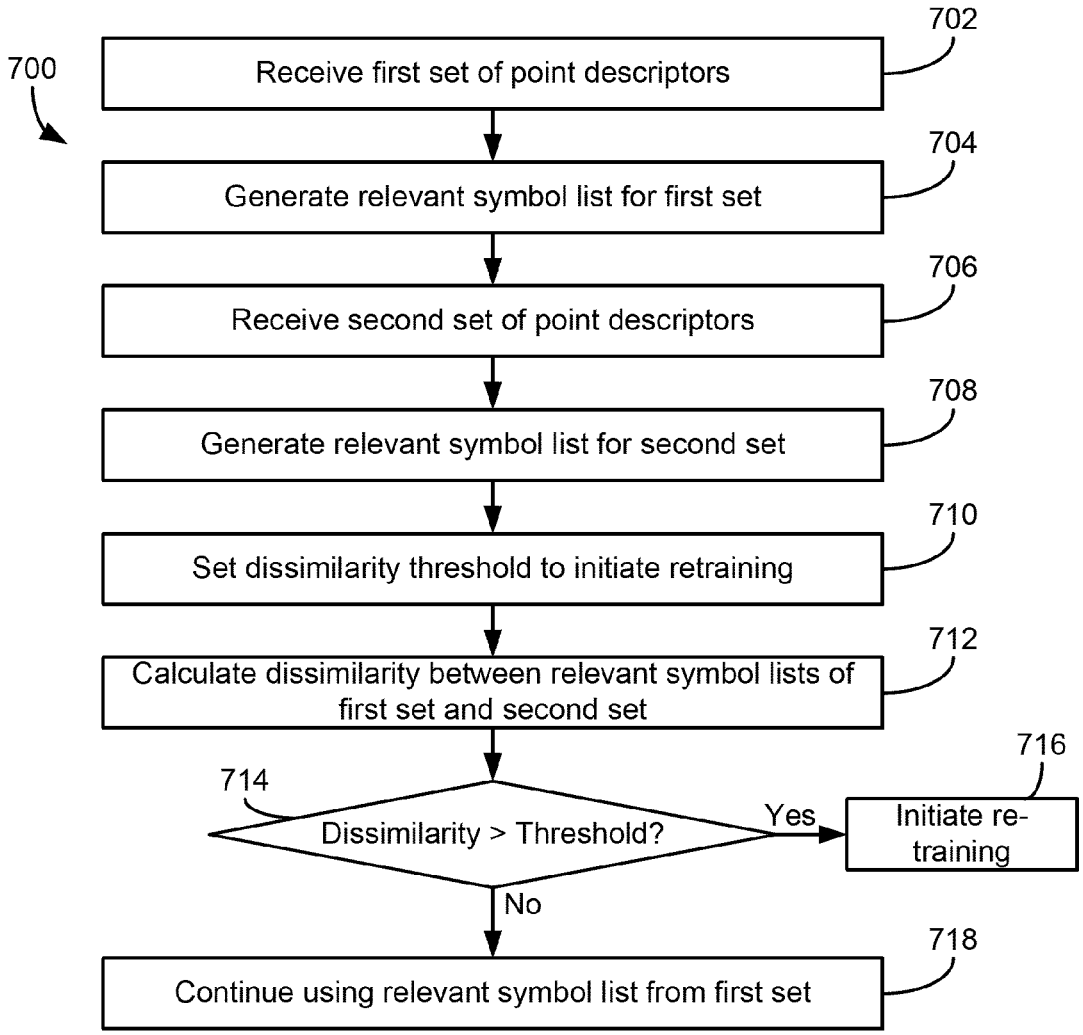

700
Receive first set of point descriptors
702
Generate relevant symbol list for first set
704
Receive second set of point descriptors
706
Generate relevant symbol list for second set
708
Set dissimilarity threshold to initiate retraining
710
Calculate dissimilarity between relevant symbol lists of first set and second set
712
714
Dissimilarity > Threshold?
Yes
Initiate re-training
716
No
Continue using relevant symbol list from first set
718

FIG. 7

SYSTEMS AND METHODS FOR CLASSIFYING DATA IN BUILDING AUTOMATION SYSTEMS

BACKGROUND

The present disclosure generally relates to the field of building automation systems. The present invention more particularly relates to systems and methods for classifying data points within a multi-point network based on processing the non-standard and semantically rich descriptions of the points.

Advanced building management system applications sometimes rely on the classification and identification of points. Conventional building management system commissioning processes rely heavily on manual point classification methods. In other words, a user manually evaluates an existing point and manually classifies the point under the schema or protocol for the new application.

Building automation systems are, in general, hardware and/or software systems configured to control, monitor, and manage devices in or around a building or building area. BAS subsystems or devices can include heating, ventilation, and air conditioning (HVAC) subsystems or devices, security subsystems or devices, lighting subsystems or devices, fire alerting subsystems or devices, elevator subsystems or devices, or other devices that are capable of automating or managing building functions, or any combination thereof.

Building automation communication standards such as BACnet and oBIX provide mechanisms to uniquely identify a data item or point within a domain of interest (e.g., within a system or a controller). The standards also allow description of the function of a data point. However, the standards are designed for human operators, not for machine processing. The human operators often decide upon a naming convention that roughly describes the location, type, or other attributes of the point. For example, a human operator might decide to name a power meter located at building C1, Floor 3, East as "BLDG-C1/ZONE/F-3/EAST/UTILS/EMETER/PWR-3," where forward slash is used as a delimiter. Despite good intentions, point names are often non-standard and difficult to parse. If the goal is assigning a discovered point to a rich functional description that an application can understand and process, the commissioning process can be very lengthy for buildings having many points. For example, given 50,000 discovered points and a conservatively quick one minute per point to review, classify, and commission, over eight hundred hours of manual investigation may be necessary to configure building points such that they will be useful to an application that relies on accurate functional classification and mapping. Because not all points are necessary for an application, points that are relevant to an application must be selected. This is also accomplished through manual investigation of naming conventions, when such conventions exist. Relevant points must be mapped into the specific equipment. For example, HVAC equipment generally comprises a set of points. Temperature sensors, cooling/heating set points, humidity, discharge air temperature, and other points, for example, may be associated with a single variable air volume (VAV) box. Conventionally, spatial relationships among points, equipments and building spaces must be manually identified and mapped.

Current building automation system naming standards lack the expressive power to (1) assign a computable semantic type description to a specific point, and (2) create a relationship among building related objects (e.g., temperature sensor, fan speed, electricity consumption, zone, equipment, etc.). Even though BACnet provides an object identifier, an object name, and an object type as mandatory attributes (e.g., character strings) to describe a point, there is no extension to describe the function of the point as an object type and to define relationships among multiple BACnet objects. Human interpretation of attributes is required to identify the function of the point for further programming or application binding. Often additional programming and nonstandard metadata management are used to support new building automation system applications.

The challenges already discussed are increased by the reality that enterprise class building automation systems are often the collection of heterogeneous building automation subsystems and devices. Furthermore, over time different building engineers may add-to or otherwise modify the system. For example, to describe outdoor air temperature, one operator may use "OAT," while another uses "Outdoor Temperature." It is also possible for multiple languages (e.g., English and Spanish) to variously be used in naming and describing a single system configuration. The uniqueness of each language makes word extraction or word segmentation extremely challenging. For example, Chinese and Japanese do not have white space to delimit characters at word boundaries. Many European languages, e.g., German, permit free form word jointing to make compound words. There are many abbreviations to shorten the description of points, and there are many variations for each abbreviation. For example, to describe zone temperature, "ZT," "ZN-T," "ZNT," and others may be used. An organization may use custom coding technology to encode data points. Such systems may be lookup based, such that a point is assigned a unique identifier, e.g., 01V001AI01.

For at least the reasons noted above, it is challenging and difficult to develop systems and methods for classifying data in building automation systems.

SUMMARY

One embodiment of the invention relates to a computerized method of assigning a building automation system point type to a plurality of unclassified data points of a building automation system. The method includes receiving, at a processing circuit, the plurality of unclassified data points and at least one attribute for each data point. The method includes receiving classifications for a first subset of the unclassified data points. Each classification associates a data point with a building automation system point type. The remaining unclassified data points form a second subset. The method includes generating a term set containing substrings that appear in the attributes of the first subset of data points. The method includes generating a first matrix describing a frequency that each of the substrings appears in the at least one attribute of the data points of the first subset. The method includes, for each of a plurality of potential building automation system point types and for each of a plurality of different substrings, calculating an indicator of a probability that the presence of the selected substring in the at least one attribute of a data point results in the data point belonging to the selected building automation system point type. The method includes assigning a building automation system point type to each data point of the second subset by finding the substring and potential building automation system point type pair having the greatest indication of probability.

Another embodiment of the invention relates to a system for assigning a building automation system point type to a plurality of unclassified data points of a building automation system. The system includes a processing circuit configured to receive the plurality of unclassified data points and at least

one attribute for each data point. The processing circuit is further configured to receive classifications for a first subset of the unclassified data points. Each classification associates a data point with a building automation system point type. The remaining unclassified data points form a second subset. The processing circuit is further configured to generate a term set containing substrings that appear in the attributes of the first subset of data points. The processing circuit is further configured to generate a first matrix describing a frequency that each of the substrings appears in the at least one attribute of the data points of the first subset. The processing circuit is further configured, for each of a plurality of potential building automation system point types and for each of a plurality of different substrings, to calculate an indicator of a probability that the presence of the selected substring in the at least one attribute of a data point results in the data point belonging to the selected building automation system point type. The processing circuit is further configured to assign a building automation system point type to each data point of the second subset by finding the substring and potential building automation system point type pair having the greatest indication of probability.

Alternative exemplary embodiments relate to other features and combinations of features as may be generally recited in the claims.

BRIEF DESCRIPTION OF THE FIGURES

The disclosure will become more fully understood from the following detailed description, taken in conjunction with the accompanying figures, wherein like reference numerals refer to like elements, in which:

FIG. **1** is a block diagram of a system for classifying data points in a building management system, according to an exemplary embodiment;

FIG. **2**A is a detailed block diagram of the learner of FIG. **1** for a naive Bayes classifier, according to an exemplary embodiment;

FIG. **2**B is a detailed block diagram of the learner of FIG. **1** for latent semantic indexing, according to an exemplary embodiment;

FIG. **3** is a detailed block diagram of the classifier of FIG. **1**, according to an exemplary embodiment;

FIG. **4** is a flow diagram of a process for probabilistically assigning building management system point types, according to an exemplary embodiment;

FIG. **5** is a more detailed flow diagram of a process for probabilistically assigning building management system point types, according to an exemplary embodiment;

FIG. **6** is a flow diagram of a process for generating a frequency matrix, according to an exemplary embodiment;

FIG. **7** is a flow diagram of a process for determining whether retraining is required, according to an exemplary embodiment.

DESCRIPTION

Before turning to the figures, which illustrate the exemplary embodiments in detail, it should be understood that the disclosure is not limited to the details or methodology set forth in the description or illustrated in the figures. It should also be understood that the terminology is for the purpose of description only and should not be regarded as limiting.

Referring generally to the Figures, a computer system for automatically classifying data points in a building automation system (BMS) is shown and described. The computer system may be utilized in conjunction with a plurality of building automation or management systems, subsystems, or as a part high level building automation system. For example, the computer system may be a part of a Johnson Controls METASYS building automation system.

The computer system includes a processing circuit configured to probabilistically classify points through frequency weighting of relevant terms used in point descriptions. The processing circuit is also configured to provide a graphical user interface for allowing a building operator to view, sort, and/or edit point descriptions and BMS point types.

Embodiments of the present disclosure are configured to automatically (e.g., via a computerized process) calculate the frequency that relevant terms appear in point descriptions belonging to the same BMS point type. The frequencies may be weighted, e.g., to account for the appearance of common descriptors (e.g., "Metasys") across all or substantially all data points. A matrix describing the frequencies can be generated. The matrix may be generated using a subset (e.g., training data) of the full dataset to be classified. From the frequency matrix, a representation of the probability that the presence of a substring in a point description attribute indicates that the point belongs to a given point type may be generated. A naive Bayes classifier, latent semantic indexing, or other classification methods, can be used to assign point types to data points in the entire dataset.

One or more embodiments described herein advantageously assign BMS point types to data points with names or descriptions that include a large number of abbreviations, non-dictionary words, and incomplete sentences. One or more embodiments also advantageously assign point types without general word-breaking rules and/or lexical analysis algorithms. One or more of the embodiments also advantageously avoid the need for new or different word-breaking rules and/or lexical analysis algorithms when additional data points (e.g., additional BAS installations or subsystems) are added to the system. One or more of the embodiments also advantageously assign point types based on terms in the point descriptions without a complete keyword dictionary or a parser that must be updated each time new data points are added to the system.

Referring now to FIG. **1**, a block diagram of system **100** for classifying data points in a building automation system is shown, according to an exemplary embodiment. System **100** includes a processing circuit **140**. Processing circuit **140** may be configured to carry out process **400** (FIG. **4**), process **500** (FIG. **5**), process **600** (FIG. **6**), process **700** (FIG. **7**), or other processes described herein.

System **100** also includes BAS installations **170**. BAS installations **170** are, in general, hardware and/or software systems configured to control, monitor, and manage devices in or around a building or building area. Subsystems or devices of BAS installations **170** can include heating, ventilation, and air conditioning (HVAC) subsystems or devices, security subsystems or devices, lighting subsystems or devices, fire alerting subsystems or devices, elevator subsystems or devices, other devices that are capable of managing building functions, or any combination thereof. Many data points may be associated with each subsystem and device of BAS installations **170**. For example, a return air temperature data point may be associated with a HVAC subsystem's return air temperature sensor. Data points are named or otherwise described with attributes or metadata in BAS installations **170**. A point description may include, e.g., an object identifier, object name, description, device type, units, or other attributes. BAS installations **170** may have many of a particular point type. For example, in a building with more than one floor, many temperatures sensors may exist per floor.

Processing circuit **140** is configured to include communications electronics **128**. Communications electronics **128** may be a network interface, and processing circuit **140** may be configured to communicate with BAS installations **170** via a network connection provided by communications electronics **128**. For example, point descriptions from BAS installations **170** may be received at processing circuit **140** via communications electronics **128**. Communications electronics **128** may be used to communicate with monitoring and reporting applications **130** and/or with client device **101**. For example, point descriptions and BMS point types may be provided to and edited point descriptions and BMS points types may be received from monitoring and reporting applications **130** and/or client device **101** via communications electronics **128**. Communications electronics **128** can be or include wired or wireless interfaces (e.g., jacks, antennas, transmitters, receivers, transceivers, wire terminals, etc.) for conducting data communications with another system or network. For example, communications electronics **128** can include an Ethernet card and port for sending and receiving data via an Ethernet-based communications network. In another example, communications electronics **128** includes a WiFi transceiver for communicating via a wireless communications network. Communications electronics **128** may be configured to communicate via local area networks or wide area networks (e.g., the Internet, a building WAN, etc.).

According to an exemplary embodiment, processing circuit **140** is integrated within a single computer (e.g., one server, one housing, etc.). In various other exemplary embodiments, processing circuit **140** can be distributed across multiple servers or computers (e.g., that can exist in distributed locations). In another exemplary embodiment, processing circuit **140** may integrated with a smart building manager that manages multiple building systems. In other embodiments, processing circuit **140** may exist relatively independently of other building automation system. Processing circuit **140** may be configured to receive and operate on data received from one or more building automation system installations **170**. The installations **170** themselves may be remote from one another and remote from processing circuit **140**.

Processing circuit **140** includes processor **150** and memory **160**. Processor **150** can be implemented as a general purpose processor, an application specific integrated circuit (ASIC), one or more field programmable gate arrays (FPGAs), a group of processing components, or other suitable electronic processing components. Memory **160** is one or more devices (e.g., RAM, ROM, Flash memory, hard disk storage, etc.) for storing data and/or computer code for completing and/or facilitating the various processes and modules described in the present disclosure. Memory **160** may be or include volatile memory or non-volatile memory. Memory **160** may include database components, object code components, script components, or any other type of information structure for supporting the various activities and information structures described in the present disclosure. According to an exemplary embodiment, memory **160** is communicably connected to processor **150** via processing circuit **140** and includes computer code for executing (e.g., by processing circuit **140** and/or processor **150**) one or more processes described herein.

Memory **160** is shown to include one exemplary embodiment of the system architecture for the point commissioning process described herein. Memory **160** is shown to include points for classification **120**. Points for classification **120** include point objects and/or point descriptors received from BAS installations **170**.

Point objects are collections of attribute values. In the discussion herein, "data point," "point," and "point object" are used interchangeably. In a dataset, the ith point p_i is a set of attribute values $a_{(i,j)}$, denoted by $p_i=\{a_{(i,1)}, \ldots, a_{(i,n)}\}$. $a_{(i,j)}$ represents the jth attribute of the ith point in a dataset. For example, a set of attributes for a BACnet analog object may include object identifier, object name, description, device type, or other attributes. A BACnet point for a return air temperature sensor, e.g., may have the following attributes (shown with example values for illustrative purposes):

Attribute Type	Value
Object Identifier	Analog Input #1101
Object Name	507_SP2.RET_AIR
Object Type	Analog Input
Present Value	68
Description	Return Air Temperature
Device Type	Thermistor
Status Flags	In_Alarm, Fault
Units	DOF
.	.
.	.
.	.

For further processing by processing circuit **100**, concatenator **121** can create a point descriptor for each point to be classified. The resulting point descriptor is an n-gram (i.e., a continuous sequence of the attributes) in the form of a concatenated string of the attribute values of the point. The point descriptor d_i of the i th point object p_i, with attributes $a_{(i,j)}$, is defined as:

$$d_i=\text{str}(a_{(i,1)})\bullet@\bullet\text{str}(a_{(i,2)})\bullet@\bullet, \ldots ,\bullet@\bullet\text{str}(a_{(i,n)})$$

where • denotes a string concatenation operator and str is a function that converts an attribute $a_{(i,j)}$ to a string. The symbol @ represents a delimiter inserted for ease of parsing in word breaking. For example, a point descriptor for the set of attributes described in the table above is:
"Analog Input #1101@507_5P2.RET_AIR@Analog Input@Return Air Temperature@Thermistor@DOF"

Concatenator **121** may omit and/or modify certain attribute values during the concatenation process. According to an exemplary embodiment, attributes values that are solely numeric are omitted from the point descriptor by the concatenator **121**. Thus, in the example above, the point descriptor did not include the attribute value "68," corresponding to the present value of the return air temperature. Omitting numeric values may advantageously reduce the data that classification and mapping module **108** parses in order to extract relevant substrings, words, symbols, or terms.

Some attributes have an abbreviation and an index (e.g., SP-2 or ZN_T-2). The index may be a numeric quantity. According to an exemplary embodiment, indices are replaced by a predefined character when the attribute value is included in a point descriptor (e.g., SP-2 becomes SP-? and ZN_T-1 becomes ZN_T-?). Modifying attributes with indices may advantageously enable classification and mapping module **108** to identify relevant patterns of substrings, words, symbols, or terms. For example, ZN_T-1 (which may stand for zone temperature sensor 1) may appear only once in a dataset (e.g., for the first zone of a building), but ZN_T-? may appear many times (e.g., for each zone temperature sensor). According to another exemplary embodiment, edit distance (i.e., character position in a substring) may be used in string similarity measurement and exclusion decisions.

A subset of points for classification **120** (i.e., a first subset) may be designated as training data **122**. According to an

exemplary embodiment, point descriptors of training data **122** are manually assigned BMS point types via a user interface presented on a display screen (e.g., on a display of client device **101**). The resulting training data **122** may be used by classification and mapping module **108** to generate or help populate an initial relevant symbol list **102**, a skip list **104**, and/or a BAS point type list **106**. In various embodiments, all or some portion of the labeled point descriptors of training data **122** are used to generate relevant symbol list **102**, skip list **104**, and/or BAS point type list **106**.

Training data **122** may also be used to train a naive Bayes classifier used to classify points as BMS point types. In some embodiments, the same set of training data **122** is used to generate relevant symbol list **102** and to train the classifier **116**. In other embodiments, different and/or overlapping sets of training data are used. In some embodiments, training data **122** is manually chosen by a BAS operator. In other embodiments, training data **122** is automatically (e.g., randomly, pseudo-randomly, etc.) chosen by classification and mapping module **108**. In other words, classification and mapping module **108** may be configured to select a representative portion of points for classification **120** for training. A representative portion may include equal or nearly equal numbers of point objects or point descriptors from a given point type and/or BAS installation. In an exemplary embodiment, classification and mapping module **108** may select training data **122** as a set of training samples $X=\{x_i \epsilon c_j | 0<i<M, 0<j<K\}$, where a training sample $\langle x_i, c_j \rangle$ comprises of a feature vector (i.e., point descriptor or concatenated string of point descriptors) x_i and a manually assigned point type, c_j. M denotes the number of training samples in X. K denotes the number of target classes in the training set.

Memory **160** includes BAS point type list **106**. BAS point type list **106** is a collection of point types to which a point may be assigned. For example, a BAS point type list may include:

Point Types
Box Heating Output
Utility Interval Consumption
Zone Temperature Setpoint
Zone Temperature
Supply Flow Setpoint
Supply Flow
Supply Fan Status
Supply Fan Output
Return Air Temperature
Occupancy
Min Outdoor Air Damper Output
Interval Demand
Interval Consumption
Heating Output
Effective Housing Setpoint
Effective Cooling Setpoint
Duct Static Pressure Setpoint
Discharge Air Temperature Setpoint
Discharge Air Temperature
Damper Position
Cooling Output
Cooling MaxFlow
.
.
.

In some embodiments, BAS point type list **106** is automatically generated using the manually-labeled points of training data **122**. In other embodiments, the point types are standardized types supported by a class of monitoring and reporting applications **130**, by an application on client device **101**, or by applications of one or more devices. In yet other embodiments, point type list **106** is based on a standard list plus manual edits. In such an embodiment, for example, a BAS operator might manually add, remove, or otherwise modify point types.

BAS ontology **124** is an information system for relating building automation system concepts and objects in a way to facilitates advanced processing tasks. BAS ontology **124** may rely upon the proper classification of points. Implementation details of indexing, retrieval, and querying of ontology is discussed in U.S. patent application Ser. No. 12/831,866, filed Jul. 7, 2010, which is hereby incorporated by reference in its entirety.

Memory **160** includes classification and mapping module **108**. Module **108** may probabilistically determine BMS point types for data points using frequency-weighted point descriptor terms. Classification and mapping module **110** may be computer code executable by processor **150**. In an exemplary embodiment, classification and mapping module **110** calculates the frequency of relevant terms in concatenated point descriptions (. Classification and mapping module **110** also generates a indicator of the probability that the appearance of one or more substrings in a point description means that the corresponding point belong to a particular BMS point type. The substrings may be found in attributes associated with the points of the building management system.

Classification and mapping module **108** is shown to include word breaker **112**. Word breaker **112** may generate a list of substrings, which are likely to indicate that a particular point belongs to a particular point type.

Classification and mapping module **108** is further shown to include learner **114**. Learner **114** may generate a matrix of the frequency with which substrings generated by word breaker **112** appear in points for classification **120**.

Classifier **116** assigns BMS point types to points of points for classification **120** when a point maximizes the probability that one or more substrings in a point descriptor indicate that the point belongs to the particular point type. GUI services **110** provides a user interface for a BAS operator to manually assign point types to points of training data **122**, generate and/or update relevant symbol list **102**, generate a frequency matrix, assign and/or update assigned point types, etc. Module **108** may receive inputs from points for classification **120**, training data **122**, and BAS ontology **124**. Module **108** may also receive and transmit data to relevant symbol list **102**, skip list **104**, learning results **118**, and annotated system configuration **126**.

Classification and mapping module **108** includes GUI services **110**. Data and processing results from classification and mapping module **108**, points for classification **120**, training data **122**, relevant symbol list **102**, skip list **104**, BAS point type list **106**, annotated system configuration **126**, etc., may be accessed by or may be pushed to a monitoring application **130** with several graphical user interface (GUI) elements (e.g., widgets, dashboard controls, windows, etc.). According to an exemplary embodiment, a user (e.g., a BAS operator) may use web-based monitoring applications **130** to view and navigate real time dashboards relating to the classification of points described herein. The GUI elements may list and/or summarize points for classification **120** and/or training data **122**. A user may utilize GUI services **110** to manually assign BMS point types to points of training data **122**. The GUI elements may also allow a BAS operator to start, modify, or end the processes for automatic generation of relevant symbol list **102**, skip list **104**, and/or BAS point type list **106**. A user may utilize GUI services **110** to manually add, remove, or modify terms or point types from lists **102**, **104**, **106**. The GUI

elements may also allow a user to view the results of the frequency calculations and probability calculations by learner **114**. A user may utilize GUI services **110** to view and/or modify the assigned point types and data points from classifier **116** and/or annotated system configuration **126**.

According to an exemplary embodiment, the GUI elements may also allow a user to map spatial relationships among points, equipment, and building spaces. For example, a user may assign location (e.g., building A, first floor, zone 1) to a zone temperature sensor associated with a zone temperature point. In some embodiment, the a list of automatically discovered points from BAS installations **170** is shown. In some embodiments, the automatically generated relevant symbol list **102**, skip list **104**, BAS point type list **104** are displayed a user. According to an exemplary embodiment, GUI elements may include a drag-and-drop interface. The interface may be configured to allow a user to drag point descriptors from a list and drop the point descriptors in an appropriate locations in a representation of a building (e.g., a two-dimensional or three-dimensional rendering the building). For example, a point descriptor for a zone temperature sensor on the east wing of the third floor of a building may be dragged from a list to a visual representation of the third floor's east wing. The interface may also be configured to assign relationship among devices and point descriptions. For example, a user may be able to draw a line (e.g., using an input device), on the visual representation of the building, connecting a temperature set-point device with corresponding air handling unit.

The user interface or report (or underlying data engine) may be configured to aggregate and categorize data points by point type, BAS installation, etc. The GUI elements may include charts or histograms that allow the user to visually analyze the data points. Processing circuit **140** may include one or more GUI servers, services, or engines (e.g., a web service) to support such applications. Further, in some embodiments, applications and GUI engines may be included outside of the processing circuit **140** (e.g., as part of a smart building manager). Processing circuit **140** may be configured to maintain detailed historical databases (e.g., relational databases, XML databases, etc.) of relevant data and includes computer code modules that continuously, frequently, or infrequently query, aggregate, transform, search, or otherwise process the data maintained in the detailed databases. Processing circuit **140** may be configured to provide the results of any such processing to other databases, tables, XML files, or other data structures for further querying, calculation, or access by, for example, external monitoring and reporting applications **130**.

Classification and mapping module **108** includes word breaker **112**. According to an exemplary embodiment, word breaker **112** receives point data from BAS installations and parses them into substrings, words, symbols, terms, etc., based on a statistical model of n-grams. Point data may be received at word breaker **112** from BAS installations **170** via communications electronics **128**. Point data may also be received from points for classification **120**. word breaker **112** may operate on the data stored in points for classification **120** or training data **122**. According to an exemplary embodiment, word breaker **112** operates on the points descriptors of training data **122**, which have manually-assigned types. According to another exemplary embodiment, word breaker **112** operates during a "learning" or "training" phase of the classification process described herein.

Word breaker **112** may operate on point data stored in training data **122** to generate one or more collections of BAS terms or symbols. These include relevant symbol list **102** and skip list **104**. Relevant symbol list **102** includes substrings, words, symbols, terms, etc., that correlate a data point and a point type. That is, the presence of one or more of the substrings on the relevant symbol list **102** in a point descriptor (e.g., attributes) may indicate a statistical likelihood that the point descriptor belongs to a certain point type. In the discussion herein, "substring," "word," "term," and "symbol" are used interchangeably, and include words, abbreviations, and alpha-numeric descriptors. The substrings may be in different languages. According to an exemplary embodiment, relevant symbol list **102** includes only substrings from training data **122**. Relevant symbol list **102** may include multiple words, symbols, terms, abbreviations, etc. (in multiple languages), corresponding to the same data type. This advantageously eliminates the needs for a grammar-, dictionary-, or language-based parser. For example, for descriptions associated with an outside air temperature sensor, the relevant symbol list may include (to the extent these terms are used in training data **122**): OAT, OT, OutsideTemp, OutsideTemperature, Außentemperaturfühler, ATF, 外部の温度センサ, 室外温度传感器, etc. Relevant symbol list **102** may include a sufficient baseline of terms to accurately (or some approximation thereof) classify points. Word breaker **112** may include a query rewriting scheme and/or word suggestions to correct for misspelled or incomplete point descriptions.

Skip list **104** includes substrings, words, symbols, terms, etc., that will not be taken into account during frequency analysis (in some embodiments, carried about by learner **114**). A symbol may be added to skip list **104** when it occurs in many training samples across point types. A high frequency may indicate that the substring is always or almost always included in BAS point descriptors and will not be useful in distinguishing between point types. For example, "BAS" may be a substring that is included in all point descriptors for a given BAS installation. Because "BAS" is not likely to indicate what point type (e.g., Supply Flow Setpoint, Supply Flow, etc.) a data point belong to, "BAS" may be added to skip list **104**.

According to an exemplary embodiment, word breaker **112** is configured to generate relevant symbol list **102**, skip list **104**, etc., automatically. In other embodiments, a user may manually add, remove, and/or modify terms in the lists. Relevant symbol list **102**, skip list **104**, etc. may include multilingual terms. Lists **102**, **104** may also include terms found from multiple BAS installations. Lists **102**, **104** may also store charts, databases, arrays, data objects, etc. that describe the terms. For example, a relational database may be used to store attributes for one or more terms, including whether they are relevant terms or terms to be skipped. Lists **102**, **104** may include past and/or current lists.

Memory **160** includes learner **114**. Learner **114** is an implementation of the probability calculation methods discussed herein. Two exemplary embodiments of learner **114** are described in greater detail in the discussions of FIGS. **2**A, **2**B. Learner **114** receives substrings from relevant symbol list **102** and point descriptions from training data **122**. In one embodiment (described in FIG. **2**A), learner **114** calculates the frequency that substrings in relevant symbol list **102** appear in attributes of training data **122**. Learner **114** also generates a matrix with columns of attributes of the same point type (concatenated into one string), rows of each substring of the relevant symbol list **102**, and individual elements of the frequency that each of the relevant substrings appear in the concatenated descriptions. Using the frequency matrix, learner **114** also generates a description of a probability, for each substring in the relevant symbol list **102**, that the presence of a substring in a description of the data point indicates that the data point belongs to a particular point type. In

another embodiment (described in FIG. **2**B), learner **114** generates a frequency matrix, similar to the one described above. Using singular value decomposition (SVD), learner **114** also decomposes the frequency matrix into three different matrices. According to an exemplary embodiment, SVD filters the non-relevant substrings within a point type. Learner **114** also reconstructs an approximated frequency matrix as the product of portions of the three decomposed matrices. Learner **114** also generates a representation of the probability (e.g., a cosine distance), between a vector associated with a relevant substring and a vector associated with point descriptors of a point type. In some embodiments of learner **114**, weighted frequencies are used to generate the frequency matrix. A BAS operator may utilize GUI services **110** to initiate, modify, end, and/or view the processes associated with learner **114**. Frequency matrices and probabilities calculations may be transmitted and stored in learning results **118**.

Memory **160** includes classifier **116**. According to an exemplary embodiment, classifier **116** is an implementation of the naive Bayes categorization discussed herein. In other embodiments, classifier **116** may be used with latent semantic indexing. Classifier **116** receives points descriptions (e.g., attributes) from points for classification **120** and representations of probability computations from learner **114**. Classifier **116** maximizes a probability that the presence of a substring from the relevant symbol list **102** in the attributes of a data point indicates that the data point belongs to a particular point type. Classifier **116** probabilistically assigns a point type from BAS point type list **106** to the point descriptors of points for classification **120** based on the maximized probability. A BAS operator may utilize GUI services **110** to initiate categorization, view the assigned point descriptions, etc. GUI services **110** may be configured to allow a BAS operator to manually reassign a point descriptor to a different point type. The assigned point types may be transmitted and stored in annotated system configuration **126**.

In some embodiments, classifier **116** may be additionally configured to determine whether further training must be completed on points for classification **120** (e.g., after additional points from BAS installations **170** have been added to points for classification **120**). Classifier **116** may do so by calculating a dissimilarity between a relevant symbol list **102** generated using a previous dataset from points for classification **120** and a relevant symbol list **102** generated using a current dataset from points from classification **120**. When further training is required, classifier **116** may transmit a command to word breaker **112** to generate a new relevant symbol list **102** using a different set of training data **122** from points for classification **120**, and learner **114** to generate a new frequency matrix and probability description using the new relevant symbol list **102**.

Memory **160** includes annotated system configuration **126**. According to an exemplary embodiment, annotated system configuration includes the results of classification and mapping module **108**. That is, annotated system configuration includes the points of BAS installations **170** and their assigned point types. Annotated system configuration may receive point descriptions from points for classification **120** and assigned point types from classifier **116**. When retraining is required, annotated system configuration **126** may transmit previous configurations (e.g., points and assigned point types) to learning results **118**. The computational results of classifier **116** from retraining may then be stored in annotated system configuration **126**.

Memory **160** includes learning results **118**. According to an exemplary embodiment, learning results **118** includes the computational results from word breaker **112**, learner **114**, classifier **116**, etc. An item ω_l, such as point descriptors, in learning results **118** may be represented as:

$$\omega_l=\langle \vartheta_l,\langle p(\vartheta_l),\langle p(\vartheta_l|c_1),p(\vartheta_l|c_2),\ldots,p(\vartheta_l|c_K)\rangle\rangle\rangle$$

where ϑ_l represents the lth symbol in a dictionary, $p(\vartheta_l)$ is the probability of ϑ_l in the training data **122**, and $p(\vartheta_l|c_K)$ is a probability that a symbol ϑ_l appears in a point type c_j. In some embodiments, learning results includes frequency matrix generated by learner **114**. Learning results may also include probability descriptions generated by learner **114**. According to an exemplary embodiment, learning results **118** may further include results from past iterations of the computations carried out by processing circuit **140**.

Referring now to FIGS. **2**A, **2**B, detailed block diagrams of learner **114** of FIG. **1** are shown, according to exemplary embodiments. The embodiment of learner **114** of FIG. **2**A may be used in classifying points using a naive Bayes model. The embodiment of learner **114** of FIG. **2**B may be used in classifying points using latent semantic indexing. One, the other, or both of the embodiments of learner **114** shown in FIGS. **2**A, **2**B may be implemented as part of classification and mapping module **108** on processing circuit **140**. In both embodiments, learner **114** may receive inputs from BAS point type list **106**, training data **122**, and relevant symbol list **102**. Learner **114** may be configured to calculate the number of times or frequency that terms in relevant symbol list appear in point descriptions of training data **122**. Learner **114** may also generate a matrix describing the frequencies. Learner **114** may also generate a representation of the probability that the presence of a substring from relevant symbol list **102** in a point description indicates that the point description belongs to a particular point type. The probability computations may be output to classifier **116**.

Referring now to FIG. **2**A, a detailed block diagram of learner **114** of FIG. **1** for a naive Bayes classifier is shown, according to an exemplary embodiment. Learner **114** includes semantic categorizer **202**. Semantic categorizer **202** receives point types from BAS point type list **102** and point descriptors from training data **122**. According to an exemplary embodiment, the point descriptors of training data **122** are manually labeled with point types. Semantic categorizer **202** organizes the point descriptors into groups or categories corresponding to the point type. For example, one or more point descriptors that belong to the zone temperature sensor point class are grouped together. The grouped point descriptors are transmitted to string concatenator **204**.

Learner **114** includes string concatenator **204**. String concatenator **204** receives point descriptors grouped according to point type from semantic categorizer **202**. According to an exemplary embodiment, string concatenator **204** concatenates point descriptors of the same type into one string. Thus, for example, if there are one hundred point descriptors in each of twenty-five point types, string concatenator **204** outputs twenty-five strings. Each string corresponds to one point type and contains the concatenated point descriptors that point type. The concatenated strings are transmitted to term frequency calculator **206** and matrix generator **210**. In other embodiments, the strings of a given BMS point type are neither grouped together by semantic categorizer **202** nor concatenated by string concatenator **204**. Rather, the point types from BAS point type list **106** and point descriptors from training data **122** are transmitted directly to term frequency calculator **206**.

Learner **114** includes term frequency calculator **206**. According to an exemplary embodiment, term frequency calculator **206** receives concatenated strings from string concat-

enator **204** and terms from relevant symbol list **122**. Term frequency calculator **204** calculates, for each substring in relevant symbol list **122** and for each concatenated string, the frequency that the substring appears in the concatenated string. The frequency $f^{c_j}(\vartheta_l)$ that substring ϑ_l occurs in BMS point type c_j is:

$$f^{c_j}(\vartheta_l) = \sum_{x=1}^{L} f_{(x,l)}^{c_j},$$

where L is the number of substrings in relevant symbol list **102**. According to an exemplary embodiment, each concatenated string corresponds to one point type. In some embodiments, the calculated frequencies are transmitted directly to matrix generator **210**. In other embodiments, the calculated frequencies are transmitted to weighted frequency calculator **208**.

Learner **114** includes weighted frequency calculator **208**. Weighted frequency calculator **208** receives calculated frequencies from term frequency calculator **206**. According to an exemplary embodiment, direct usage of a raw frequency in estimating probability may falsely emphasizes certain features. This may be true, for example, if a symbol occurs in many point types (i.e., this symbol has a high frequency). As a result, the symbol will tend to incorrectly emphasize the points that contain the symbol. For example, a point description may include the customer name and a building floor level. Both the customer name and building floor level may have a high number of occurrences and may not be good features to classify the descriptor. The relevance of a irrelevant symbol in classification can be reduced. To do so, a frequency weighting scheme may be applied before converting raw frequencies into probabilities. According to an exemplary embodiment, inverted document frequency is to panelize irrelevant terms. The inverse measure of the informativeness $idf(\vartheta_l)$ of a symbol ϑ_l is

$$idf(\vartheta_l) = \log\left(\frac{N}{df(\vartheta_l)}\right),$$

where N is the total number of symbols observed from the training set and $df(\vartheta_l)$ is the number of point descriptors containing a symbol ϑ_l. Applying invented document frequency to the term frequency calculation (as described in the discussed of term frequency calculator **206**), the weighted frequency of a symbol ϑ_l is

$$f_{(x,y)}' = f_{(x,y)} \times idf(\vartheta_l).$$

According to an exemplary embodiment, the weighted frequency is calculated for each symbol in relevant symbol list **102** across the concatenated strings for each point type. The weighted frequencies are transmitted to matrix generator **210**.

Learner **114** includes matrix generator **210**. According to an exemplary embodiment, matrix generator **210** receives concatenated strings from string concatenator **204** and weighted frequencies from weighted frequency calculator **208**. Matrix generator **210** constructs an M by K matrix A:

$$A = \begin{bmatrix} f'_{(1,1)} & \cdots & f'_{(M,1)} \\ \vdots & \ddots & \vdots \\ f'_{(1,K)} & \cdots & f'_{(M,K)} \end{bmatrix},$$

where M is the number of training samples in the set of training samples X (i.e., the number of concatenated strings of point descriptors) and K is the number of target classes in a training set (i.e., the number of symbols in relevant symbol list **102**). Each element represents the weighted frequency $f_{(x,y)}'$ of a symbol in a concatenated string of point descriptors. Each row represents occurrences of a symbol across strings of point descriptors. Each column represents the frequency of symbols in a string of point descriptors. According to an exemplary embodiment, the initial values of A are filled with 1.0, to prevent divide by zero error. In some embodiments, matrix generator **210** receives un-weighted frequencies from term frequency calculator **206**. In other embodiments, matrix generator **210** receives point descriptors along with manually assigned point types (but not concatenated strings) from training data **122**. In such an embodiment, a matrix may be constructed by matrix generator **210**, with each element corresponding to the frequency of a symbol, a point descriptor, and a point type. Matrix generator **210** transmits the constructed matrix A to probability calculator **212**. In some embodiments, matrix generator **210** transmits matrix A to learning results **118**.

According to an exemplary embodiment, and as described below, latent semantic indexing may be generate a matrix A. Matrix A may be deconstructed using singular value decomposition, as described below. A portion of the deconstructed matrices may be used to reconstruct a matrix A', which is an approximation of matrix A. Matrix A' may be used in place of matrix A in the discussion herein.

Learner **114** includes probability calculator **212**. Probability calculator **212** receives frequency matrix A or matrix A' from matrix generator **210**. Probability calculator **212** uses frequency matrix A or matrix A' to calculate the probability $p(\vartheta_l)$ of the frequency of a symbol ϑ_l in a training sample (i.e., a concatenated string):

$$p(\vartheta_l) = \frac{\sum_{x=1}^{L} f'_{(x,y)}}{\sum_{x=1}^{L}\sum_{y=1}^{M} f'_{(x,y)}},$$

where $f_{(x,y)}'$ is the weighted frequency of a symbol in a training sample (i.e., a concatenated string), L is the number of symbols in relevant symbol list **102**, and M is the number of training samples in the set of training samples X (i.e., the number of concatenated strings of point descriptors).

According to an exemplary embodiment, probability calculator **212** generates a description of the probability that the presence of one of the terms in relevant symbol list **102** in a representation of a data point indicates that the data point belongs to a particular point type. That is, probability calculator **212** also uses frequency matrix A or matrix A' to calculate the probability $p(\vartheta_l|c_K)$ that a symbol ϑ_l appears in a class c_j:

$$p(\vartheta_L \mid c_j) = \frac{f^{c_j}(\vartheta_l)}{n_j},$$

where $f^{c_j}(\vartheta_l)$ is the frequency of a symbol ϑ_l in point type c_j (as described in the discussion of term frequency calculator **206** and weighted as described in the discussion of the weighted frequency calculator **208**).

$$n_j = \sum_{x=1}^{L} \sum_{r=1}^{M} f_{(x,y)}^{c_j}$$

and is the total occurrence of all symbols in the training sample (i.e., concatenated string) labeled c_j. The probability $p(\vartheta_l|c_K)$ that symbol ϑ_l appears in class c_j is transmitted to classifier **116**. In some embodiments, probability calculator **212** transmits probability $p(\vartheta_l|c_K)$ to learning results **118**.

Referring now to FIG. **2**B, a detailed block diagram of learner **114** of FIG. **1** for latent semantic indexing (LSI) is shown, according to an exemplary embodiment. LSI is a semantic sensitive document clustering technique that captures and preserves recurring term usage patterns. LSI maps documents and queries into a lower dimensional space. LSI involves the creation of a term to document matrix A. The matrix A is an u by v matrix, where u is the number of documents (e.g., concatenated strings corresponding to point types), and v is the number of terms (e.g., from relevant symbol list **102**) observed from a document collection (set of concatenated strings). The matrix A described in this paragraph may be similar to the matrix A described in the discussion of matrix generator **210** (FIG. **2**A). Semantic categorizer **202**, string concatenator **204**, term frequency calculator **206**, weighted frequency calculator **208**, and matrix generator **210** of FIG. **2**B are substantially as described in the discussion of FIG. **2**A.

In the embodiment of FIG. **2**B, learner **114** additionally includes singular value decomposition (SVD) **214**. SVD **214** receives a term to document matrix A from matrix generator **210**. SVD **214** includes term eigenvector generator **216**, diagonal matrix generator **218**, and point description eigenvector generator **220**. By using SVD, matrix A can be decomposed into the product of three different matrices: the term eigenvector U; the diagonal matrix of singular values S; and the point description eigenvector V^T. Generators **216**, **218**, **220** construct matrices U, S, and V^T, respectively. U is a matrix of eigenvectors derived from a term-to-term similarity matrix defined in the document space by measuring correlation. (The term-to-term similarity matrix serves similar role of the covariance matrix in principal component analysis.) V^T is a matrix of eigenvectors derived from a document-to-document (i.e., concatenated string-to-concatenated string) similarity matrix defined in the term space by comparing a term profile of a document. S is an r by r diagonal matrix of singular values, where r is the rank of A. Matrices U, S, and V^T may be referred to as the second, third, and fourth matrices respectively. SVD **214** transmits the matrices U, S, and V^T to matrix reconstructor **222**. In other embodiments, more, fewer, or different matrices are transmitted to matrix reconstructor **222**.

In the embodiment of FIG. **2**B, learner **114** includes matrix reconstructor **222**. Matrix reconstructor **222** receives matrices U, S, and V^T from SVD **214**. Matrix reconstructor **222** is configured to construct a matrix A' that approximates term to document matrix A. Matrix A' may be referred to as the fifth matrix. Matrix A can be approximated by keeping first k singular values from S, and the corresponding columns from U and V^T. k is the approximation quality control constant. k should be large enough to allow for fitting of the characteristics of the data and small enough to eliminate the non-relevant representational details. According to an exemplary embodiment, k is set to 70%. In other embodiments, k may be greater than or less than 70%. Approximation of the original term-to-document matrix A can be obtained by

$$A' = U_k S_k V_k^T \cong A,$$

where U_k and V_k^T represent matrixes that keep the first k columns from U and V^T, and S_k is a matrix that has the first k singular values. Matrix reconstructor **222** transmits matrix A' to similarity calculator **224**. In some embodiments, matrix A' may be transmitted to learning results **118**.

With a careful selection of k (e.g., determined by evaluating precision and recall), SVD provides a modified vector space, where non-relevant terms within a BMS point type are filtered. Transitive co-occurrence of terms is captured by measuring the correlations among terms, while principal component analysis (PCA) uses covariance analysis. LSI assumes that there are strong associations between terms in text. According to an exemplary embodiment, such associations exist in the building management data point classification domain. Eventually, the dimension reduction step in LSI captures the semantic relationships by analysis of term co-occurrences. The dimension reduction step modifies the component matrices in such a way that terms observed in some documents may appear with greater or lesser estimated frequency and some non-observed terms in the input may appear (at least fractionally).

According to an exemplary embodiment, matrix A' is used to calculate the probability $p(\vartheta_l)$ of the frequency of a symbol ϑ_l in a training sample (i.e., a concatenated string). Matrix A' may also be used to calculate the probability $p(\vartheta_l|c_K)$ that a symbol ϑ_l appears in a class c_j. Thus, the methods and systems described herein may advantageously utilize latent semantic indexing in conjunction with a naive Bayes classifier.

In the embodiment of FIG. **2**B, learner **114** includes matrix similarity calculator **224**. Similarity calculator **224** may receive approximated term-to-document matrix A' from matrix reconstructor **222**. Similarity calculator **224** generates a representation of the probability that the presence of one of the terms in relevant symbol list **102** in a description of a data point indicates that the data point belongs to a particular point type. The probability may be represented by a cosine distance, which measures the probability based on an angle between a query and a target vector. The similarity or cosine distance $\delta(q,t_k)$ between a query vector q (representing a substring in relevant symbol list **102**) and a training sample vector t_k (representing a concatenated string of point descriptors in a given class) is:

$$\delta(q, t_k) = \cos(\theta) = \frac{q \cdot t_k}{\|q\| \cdot \|t_k\|}$$

The similarity or cosine distance $\delta(q,t_k)$ may be transmitted to classifier **116**. In some embodiments, matrix similarity calculator **224** may transmit similarity or cosine distance $\delta(q,t_k)$ to learning results **118**.

Referring now to FIG. **3**, a detailed block diagram of classifier **116** of FIG. **1** is shown, according to an exemplary embodiment. Classifier **116** of FIG. **3** may be configured to classify points using a naive Bayes model or latent semantic

indexing. In other embodiments, different methods may be used. Classifier **116** may be implemented as part of classification and mapping module **108** on processing circuit **140**. Classifier **116** may receive input from relevant symbol list **102**, BAS point type list **106**, points for classification **120**, and training data **122**. Classifier **116** may determine a maximum probability that the presence of a substring from the relevant symbol list **102** in the description of a data point indicates that the data point belongs to a particular point type. Classifier **116** assigns a point type from BAS point type list **106** to the point descriptors of points for classification **120** based on the probabilistic determination. Classifier **116** may also be configured to determine whether retraining is required. The assigned point type may be output to GUI services **110** and annotated system configuration **126**.

Classifier **116** includes dissimilarity calculator **302**. Dissimilarity calculator **302** receives symbols from relevant symbol list **102** and point descriptors from points for classification **120**. According to an exemplary embodiment, dissimilarity calculator **302** determines whether retraining is required. Retraining may include generation of a new relevant symbol list **102**, frequency matrix, and probability representation. Retraining is required when the terms used in the point descriptors of points for classification **120** are sufficiently (i.e., beyond a threshold amount) different from the terms in relevant symbol list **102**. This indicates that the classification and mapping module **108** is less than well-suited, with the then-existing relevant symbol list **120**, frequency matrix, and probability representation, to probabilistically classify points based on the symbols in the point descriptors. In some embodiments, dissimilarity calculator **302** may be provided as part of classifier **116**. In other embodiments, dissimilarity calculator **302** may be provided as part of learner **114** or as a separate component of classification and mapping module **108**.

The need for retraining may arise, e.g., with a new set of points that is added to points for classification **120**. For example, a new BAS installation (with a new set of data points) may be added to the system with processing circuit **140**. In some embodiments, the need for new training is determined based on how many symbols have been seen or not been seen by classifier **116**. Given a new set of points, keyword and symbol extraction is performed by, e.g., word breaker **112**. Keyword and symbol extraction is described in the discussion of word breaker **112** and results in a new list of relevant symbols. B is a new set of vocabularies (i.e., keywords, symbols, terms, etc.) from the new set of points (i.e., new query) to be classified and D is the set of terms (e.g., relevant symbol list **102**) obtained during the training phase. The dissimilarity between D and B can be measured with the following form:

$$(B, D) = \frac{|B \cup D| - |B \cap D|}{|B \cup D|} = 1 - \frac{|B \cap D|}{|B \cup D|}.$$

This is the Jaccard index or dissimilarity, which measures the complementary rate of intersection of two sets. If two sets are identical (i.e., the terms from both sets of points are identical), then the equation equals one. If an intersection of two sets is empty (i.e., the two sets of the points share no terms), then the equation equals zero. A thresholding parameter (e.g., (B,D) =0.3) can be used to determine when a classifier needs additional training. When retraining is required, a notification may be provided to GUI services **110**. Dissimilarity calculator may also provide commands to, e.g., word breaker **112** to generate a new relevant symbol list and learner **114** to generate a new frequency matrix and/or probability description. When retraining is not required, dissimilarity calculator **302** may provide a command to point type assignor **304** to probabilistically assign point types to points for classification **120**. In other embodiments, a different method (other than calculating the Jaccard dissimilarity between relevant terms of two sets of points) may be used to determine when retraining is required.

Classifier **116** includes point type assignor **304**. Point type assignor **304** receives point descriptors from points for classification **120**, point types from BAS point type list **106**, and probability descriptions from learner **114**. According to an exemplary embodiment, point type assignor **304** probabilistically assigns point types (from BAS point type list **106**) to point descriptors (from points for classification **120**) using probability representations (from learner **114**). A point type that maximizes the value of the probability representation is assigned to the particular point. The assigned point types are transmitted to GUI services **110** and/or annotated system configuration **126**.

In some embodiments, point type assignor **304** is a naive Bayes classifier. Naive Bayes is an efficient and effective inductive learning algorithms for machine learning and data classification. Typically, an example X (e.g., a set of concatenated strings) is represented by a tuple of attribute values $X = \langle x_1, x_2, \ldots x_n \rangle$, where x_i (e.g., one concatenated string) is the value of ith attribute of example X. C represents the classification variable, and c is the value (e.g., a point type label) of C. Calculation of probability of example X becomes class c is:

$$p(c \mid X) = \frac{p(X \mid c)p(c)}{P(E)}.$$

According to an exemplary embodiment, all attributes (e.g. words in a document) are independent given a class label of the class variable. Then p(X|c) is equivalent to

$$p(X \mid c) = p(x_1, x_2, \ldots, x_n \mid c) = \prod_{i=1}^{n} p(x_i \mid c)$$

Example X may be classified by finding a class value c_j that maximizes the above equation. That is,

$$\text{classify}(X) = \arg\max\left(\prod_{i=1}^{n} p(x_i \mid c_j)\right), 0 < j < K,$$

where K is the number of possible class values (e.g. a number of point types).

In the embodiment of FIG. **3**, the point type assignor may be a naive Bayes classifier of the form:

$$\text{classify}(X) = \arg\max_{j}\left(\prod_{i=1}^{n} p(\vartheta_i \mid c_j)\right), 0 < j < K,$$

where $p(\vartheta_i|c_K)$ is the probability that symbol ϑ_i appears in class c_j, received from the probability calculator **212**. Point type assignor **304** assigns, to a point descriptor, the point type

that maximizes the equation. Various mathematical methods may be used to compute the naive Bayes classifier. In other embodiments, point type assignor **304** is a classifier for latent semantic indexing. Point type assignor **304** assigns to a point descriptor the point type that maximizes the similarity or cosine distance $\delta(q,t_k)$, as described in the discussion of similarity calculator **116**. The similarity or cosine distance may have a maximum value of one. A point type that maximizes the cosine distance results in the cosine distance approach (or reaching) one.

Referring now to FIG. **4**, a flow diagram of a process **400** for probabilistically assigning point types is shown, according to an exemplary embodiment. Process **400** may be implemented on, e.g., processing circuit **140**. In some embodiments, steps **402-406** of process **400** may be characterized as a "learning" or "training" phase. Steps **402-406** may operate on a subset of data, whereas step **408** operates on a full set of data (e.g., all point descriptors from BAS installations **170**). Process **400** may be a high-level representation of the process described in more detail in FIGS. **5** and **6**.

Process **400** includes assigning point types to point descriptors in training data (**402**). According to an exemplary embodiment, the point types are assigned manually (e.g., by a BAS operator). A BAS operator may use one or more GUIs provided by GUI services **110** to assign point types. The point types may include those enumerated in the discussion of BAS point type list **106** (FIG. **1**). The point descriptors in training data may be a subset of all the point descriptors in the full dataset (e.g., across all BAS installations). Step **402** may advantageously reduce the number of points that are required to be manually assigned compared to the current process, which involves complete manual classification of points. According to an exemplary embodiment, the training data may be selected so that the manually-assigned point descriptors are evenly or nearly evenly distributed across point types, physical location (e.g., BAS installation), etc.

Process **400** includes determining a weighted frequency matrix for relevant symbols in the point descriptors in the training data (**404**). Relevant symbols may be those identified by, e.g., processing circuit **140**, to most likely indicate what BMS point type a point belongs to. That is, the presence of the symbol in the point description increases the probability that the corresponding point belongs to a particular point type. Relevant symbols may be determined by word breaker **112** and stored in relevant symbol list **104** (FIG. **1**). Processing circuit **140** may calculate at what frequency the symbols occur in each of the point descriptors in the training data. In some embodiments, the points descriptors of the same class are concatenated into one string. In such embodiments, term frequency calculator **206** calculates the frequency that the relevant symbols occur in the strings for each point type. In some embodiments, the calculated frequency may be weighted so that it more accurately represents the utility of a substring in indicating what point type a data point is. For example, a large proportion of points in a dataset may include general substrings, such as "BAS." Because the substring BAS is unlikely to suggest what point type the point belongs to, it is less useful than other terms, such a "ZN_T-?" (indicating zone temperature). Using the calculated frequency alone may overemphasize commonly-appearing, but less relevant terms. According to an exemplary embodiment, inverted document frequency (IDF) is used to weight the frequencies. Processing circuit **140** may be configured to generate a matrix of the weighted frequencies. According to an exemplary embodiment, matrix generator **210** constructs a matrix with columns of point descriptions of the same point type (concatenated into one string), rows of each substring of the relevant symbol list **102**, and individual elements of the weighted frequency that relevant symbols appear in the concatenated descriptions.

According to an exemplary embodiment, latent semantic indexing may be used in conjunction with a naïve Bayes classifier. A matrix A' may be generated using latent semantic indexing. Matrix A' may then be used to calculate the probability $p(\vartheta_I)$ of the frequency of a symbol ϑ_I in a training sample (i.e., a concatenated string) and the probability $p(\vartheta_I|c_K)$ that a symbol ϑ_I appears in a class c_j.

Process **400** includes generating a representation of the probability of correlation between relevant terms and point types (**406**). The representation describes the probability that the presence of one or more relevant terms in a description of a data point indicates that the data point belongs to one of a plurality of point types. In some embodiments, for example, when a naive Bayes classifier is used, a probability $p(\vartheta_I|c_K)$ that symbol ϑ_I appears in class c_j is calculated. This is described in more detail in the discussion of probability calculator **212** (FIG. **21**). In other embodiments, for example, when latent semantic indexing is used to classify points, a similarity or cosine distance $\delta(q,t_k)$ between a query vector q (representing a substring in relevant symbol list **102**) and a training sample vector t_k (representing a concatenated string of point descriptors in a given class) is generated. This is described in more detail in the discussion of similarity calculator **224** (FIG. **2**B).

Process **400** includes assigning point types to points in the full dataset (**408**). The "full dataset" may include all of the points in points for classification **120** or all of the points of BAS installations **170**. In other embodiments, a BAS operator may designate a portion of points for classification **120** and/or BAS installations **170** to be assigned point types. According to an exemplary embodiment, the full dataset includes more points than the training dataset. This advantageously obviates the need for manually assigning point types to all points of BAS installations **170**. Processing circuit **140** assigns point types by determining a point type-substring pair that maximizes a probability that the presence of the substring in the description of the data point indicates that the data point belongs to the point type. In some embodiments, a naive Bayes classifier may be used. In other embodiments, for example, with latent semantic indexing, a similarity or cosine distance $\delta(q,t_k)$ may be maximized.

Referring now to FIG. **5**, a more detailed flow diagram of a process **500** for probabilistically assigning point types is shown, according to an exemplary embodiment. Process **500** may be implemented on, e.g., processing circuit **140**. In some embodiments, steps **504-514** of process **500** may be characterized as a "learning" or "training" phase. Steps **504-512** may operate on one or more subsets of data, whereas step **514** operates on a full set of data (e.g., all point descriptors from BAS installations **170**). Process **500** may be a more low-level description of the process described in FIG. **4**.

Process **500** includes receiving a first set of point descriptors (**502**). The point descriptors may be received at processing circuit **140** from BAS installations **170**. The point descriptors may be stored in points for classification **120**. In some embodiments, data points (and not point descriptors) may be received at processing circuit **140**. Processing circuit **140** may modify (e.g., as described in the discussion of points for classification **120**) and concatenate the attribute values for each of the points, and store the now-point descriptors in points for classification **120**.

Process **500** includes selecting a first subset of the first set of point descriptors for training (**504**). According to an exemplary embodiment, the first subset is a proportion of point

descriptors selected by a BAS operator. The first subset may be designated by a BAS operator at a user interface generated by GUI services **110** (FIG. **1**). The first subset may be stored as training data **122**.

Process **500** includes assigning point types to the first subset of point descriptors (**506**). According to an exemplary embodiment, the point types are manually assigned to the subset. The point types may include those enumerated in the discussion of BAS point type list **106**. Manually assigning point types to only a subset of point descriptors and probabilistically assigning classes to the remaining point descriptors eliminates the need to manually label all of the point descriptors. This may advantageously reduce the time, error, etc., associated with completely manual point classification. A BAS operator may use a user interface generated by GUI services **110** (FIG. **1**) to label the point descriptors. The labeled point descriptors may be stored as training data **122**.

According to an exemplary embodiment, process **500** continues with "classifier training," including steps **508-512**, which are described in more detail below. In some embodiments, all of the labeled point descriptors (i.e., the first subset selected in step **504**) are used in classifier training. That is, all of the point descriptors that are manually labeled are used to generate a relevant symbol list, frequency matrix, and probability description. In other embodiments, a fewer than all of the labeled point descriptors may be used for classifier training. For example, from the nineteen thousand points (the first subset) that were manually assigned point types, six thousand may be selected for classifier training. The subset that is selected for classifier training may be evenly or near-evenly distributed across point types, physical locations (e.g., BAS installations), etc.

Process **500** includes generating a relevant symbol list using the subset of labeled point descriptors (**508**). The relevant symbol list may be described as a first plurality of terms. The relevant symbol list includes substrings, words, symbols, terms, abbreviations, etc. (in multiple languages) that are extracted from the point descriptors. As described in the discussion of word breaker **112** (FIG. **1**), relevant symbol list **102** (FIG. **1**), and step **404** of process **400** (FIG. **4**), the relevant symbol list contains substrings that are probabilistically likely to indicate that a point descriptor containing the substring belongs to a particular point type. According to an exemplary embodiment, the relevant symbol list is generated by word breaker **112** and stored as relevant symbol list **102** (FIG. **1**). In some embodiments, a skip list may also be generated (as described in the discussion of word breaker **112** and skip list **104**). The skip list contains substrings that are determined to be not relevant in determining whether a point descriptor belongs to a particular BMS point type.

Process **500** includes generating a frequency matrix (**510**). As described in the discussions of matrix generator **210** (FIG. **2**A) and step **404** of process **400** (FIG. **4**), a frequency matrix includes the frequency that each of the symbols in the relevant symbol list appears in descriptions of the labeled data points. In some embodiments, the frequencies may be weighted (e.g., using inverted document frequency). In some embodiments, the point descriptors of a given point type may be concatenated into one string. According to an exemplary embodiment, matrix generator **210** (FIG. **2**A, **2**B) constructs the frequency matrix. The process for generating the frequency matrix is described in more detailed in the discussion of FIG. **6**. according to an exemplary embodiment, the frequency matrix may be generated using latent semantic indexing.

Process **500** includes generating a probability representation (**514**). As described in the discussions of probability calculator **212** (FIG. **2**A), similarity calculator **224** (FIG. **2**B), and step **406** of process **400** (FIG. **4**), the probability description describes the likelihood that the presence of one or more symbols in a point descriptor indicates that the point descriptor belongs to a particular point type. The probability description may be of the form $p(\vartheta_l|c_K)$, i.e., the probability that symbol ϑ_l appears in BMS point type c_j. This description may be used when classifying points using a naive Bayes method. The probability description may also be of the form $\delta(q,t_k)$ (describing a similarity or cosine distance). This description may be used when classifying points using latent semantic indexing. The probability description may be generated by probability calculator **212** (FIG. **2**A) or similarity calculator **224** (FIG. **2**B), and may be based on the frequency matrix generated in step **510**.

Process **500** includes classifying points descriptors in the first set (**514**). The first set of point descriptors includes the first subset, the second subset, and/or additional point descriptors. The first subset includes the manually labeled point descriptors. The second subset includes the unlabeled point descriptors. Process **500** and other methods described herein thus advantageously classify points of the second subset in an automated manner. According to an exemplary embodiment, the points are classified probabilistically, based on the representation generated in step **512**. As described in the discussions of point type assignor **304** (FIG. **3**) and step **408** of process **400** (FIG. **4**), a point type is assigned to a data point descriptor when the particular point type maximizes a probability that substrings in the point descriptor indicate that the data point belongs to the point type. This may be a substring-point type pair that has the greatest indication of probability. In some embodiments, a naive Bayes classifier is used. Processing circuit **140** assigns BMS point types based on calculating:

$$\text{classify}(X) = \arg\max_j \left(\prod_{l=1}^{n} p(\vartheta_l \mid c_j) \right), \; 0 < j < K.$$

Various mathematical methods may be used to compute the naive Bayes classifier. In other embodiments, for example, when latent semantic indexing is used, processing circuit **140** maximizes a similarity or cosine distance $\delta(q,t_k)$ between a query vector q (representing a substring in relevant symbol list **102**) and a training sample vector t_k (representing a concatenated string of point descriptors in a given class).

Referring now to FIG. **6**, a flow diagram of a process **600** for generating a frequency matrix is shown, according to an exemplary embodiment. Process **600** may be implemented on, e.g., processing circuit **140**. Process **600** describes step **512** of process **500** (FIG. **5**) in more detail. In other embodiment, different methods may be used to generate the frequency matrix. For example, latent semantic indexing may be used.

Process **600** includes concatenating points descriptors of a given point type (**602**). According to an exemplary embodiment, the manually-labeled point descriptors are grouped by point type. This may be done by semantic categorizer **202** (FIG. **2**A, **2**B). String concatenator **204** concatenates the point descriptors of a given type into one string. A string of point descriptors D_{c_j} for a j th point type c_j is

$$D_{c_j} = d_{(c_j,1)} \bullet @ \bullet d_{(c_j,2)} \bullet @ \ldots @ \bullet d_{(c_j,n)},$$

where $d_{(c_j,i)}$ is the ith point descriptor manually assigned to point type c_j, • is a string concatenation operator, and @ is a delimiter. Each point type may be associated with one string of point descriptors. Concatenating the strings of a given type

may advantageously reduce the size of matrix generated using the strings (as described in step **606**). In turn, this may advantageously decrease the size of memory **160** (FIG. **1**), which may store data representing the matrix. In other embodiments, point descriptors of a given type may not be concatenated, and the frequency matrix may be generated (as described in step **606**) with each element corresponding to the frequency of a symbol, the point descriptor, and the point type.

Process **600** includes calculating the frequency of relevant terms across BMS point types (**604**). As described in the discussion of term frequency calculator **206** (FIG. **2**A) and step **404** of process **400** (FIG. **4**), for each relevant symbol and for each concatenated string of point descriptors, the frequency that a relevant symbol appears in a concatenated string is calculated. Frequency calculator **206** (FIG. **2**A) may calculate the frequencies. Because the concatenated strings represent point types (as described in step **602**), calculating the frequency of the symbols across the concatenated strings is equivalent to calculating the frequency across point types. According to an exemplary embodiment, the calculated frequencies are weighted using an inverted document frequency factor. This is described in the discussion of weighted frequency calculator **208** (FIG. **2**A).

Process **600** includes constructing a frequency matrix with the relevant symbols, concatenated strings, and weighted frequencies (**604**). The frequency matrix may be described as the first matrix. As described in the discussion of matrix generator **210** and step **404** of process **400** (FIG. **4**), the frequency matrix is constructed with columns of concatenated descriptions (i.e., each column corresponds to a different concatenated description or a different point type), rows of relevant substrings (i.e., each row corresponds to a different relevant substring), and individual elements of the weighted frequency that each of the relevant substrings appears the concatenated descriptions. Matrix generator **210** may construct the frequency matrix.

Referring now to FIG. **7**, a flow diagram of a process **700** for determining whether retraining is required, according to an exemplary embodiment. Process **700** determines whether the relevant symbol list (from step **510** of process **500**), frequency matrix (from step **512** of process **500**), and probability description (from step **514** of process **500**) are sufficiently representative of the points being classified. That is, process **700** determines whether the terms that are used in the points to be classified are similar enough to the terms used to generate the relevant symbol list, frequency matrix, and probability description, such that the points will be classified accurately. If there is too much divergence between the terms used in the current points for classification and the terms used to generate the relevant symbol list, frequency matrix, and probability description, retraining may be initiated. Process **700** may be implemented on, e.g., processing circuit **140**. According to an exemplary embodiment, process **700** may be completed prior to probabilistically assigning point types. This may advantageously ensure that point types are assigned by a classifier that is representative of the terms used in the points for classification.

Process **700** includes receiving a first set of point descriptors (**702**) and a second set of point descriptors (**706**). The first set and second set may each be pluralities of unclassified data points. The point descriptors (or data points, in some embodiments) may be received from BAS installations **170**. Steps **702**, **704** are substantially as described in the discussion of step **502** of process **500** (FIG. **5**). According to an exemplary embodiment, the second set of point descriptors may be received at some time after the first set of point descriptors is received. During that intervening time, the number and/or content of the point descriptors from BAS installations **170** may have changed. For example, the second set may include additional point descriptors that were not present in the first set. This may be the case when additional BAS installations are brought on line. In another example, the second set may include fewer point descriptors than in the first set. However, the second set may include point descriptors with terms that did not appear in the first set. This may be the case when integrating heterogeneous building automation systems (i.e., those using different point description vocabularies).

Process **700** includes generating relevant symbol lists for the first set (**704**) and the second set (**708**) of point descriptors. Steps **704**, **708** may be substantially as described in step **510** of process **500** (FIG. **5**). Note that steps **702** (receiving the first set) and **704** (generating a relevant symbol list for the first) maybe completed as part the ordinary process for classifying point descriptors of the first set (as described by, e.g., process **400** and process **500**). The relevant symbol list generated for the first set may be valid for one or more sets of points for classification. However, once a number and/or content of the points of classification have changed beyond a certain threshold, the relevant symbol list for the first set of point descriptors may no longer be optimal.

Process **700** includes setting a dissimilarity threshold (**710**). According to an exemplary embodiment, a quantity may be calculated representing the dissimilarity of the relevant symbol list from the first set of point descriptors and the second set of point descriptors. The dissimilarity threshold describe the point at which retraining is initiated. Process **700** includes calculating the dissimilarity between the relevant symbol lists for the first set and second set (**712**). According to an exemplary embodiment, the dissimilarity is calculated using Jaccard dissimilarity. This is described in the discussion of dissimilarity calculator **302** (FIG. **3**). If two lists are identical (i.e., the same terms are used in both sets), then the Jaccard dissimilarity equals one. If the intersection of two sets is empty (i.e., none of the same terms are used in the two sets), then the Jaccard dissimilarity equals zero. The thresholding parameter may be set between zero and one (step **710**). A thresholding parameter that is closer to zero allows greater tolerance for differences between the two relevant symbol lists, and retraining occurs less frequently. A thresholding parameter that is closer to one allows less tolerance for differences between the two lists, and retraining occurs more frequently.

Process **700** includes comparing the calculated dissimilarity to the threshold (**714**). If the calculated dissimilarity is greater than the threshold, then retraining may be initiated (**716**). The need for retraining may be reported to a user interface generated by GUI services **110**. In some embodiments, retraining starts automatically (without a manual input). In other embodiments, the input of a BAS operator is required to start retraining. When the calculated dissimilarity is less than the threshold, the relevant symbol list from the first set may be continued to be used in the classification of points (**718**).

The construction and arrangement of the systems and methods as shown in the various exemplary embodiments are illustrative only. Although only a few embodiments have been described in detail in this disclosure, many modifications are possible (e.g., variations in sizes, dimensions, structures, shapes and proportions of the various elements, values of parameters, mounting arrangements, use of materials, colors, orientations, etc.). For example, the position of elements may be reversed or otherwise varied and the nature or number of discrete elements or positions may be altered or varied.

Accordingly, all such modifications are intended to be included within the scope of the present disclosure. The order or sequence of any process or method steps may be varied or re-sequenced according to alternative embodiments. Other substitutions, modifications, changes, and omissions may be made in the design, operating conditions and arrangement of the exemplary embodiments without departing from the scope of the present disclosure.

The present disclosure contemplates methods, systems and program products on any machine-readable media for accomplishing various operations. The embodiments of the present disclosure may be implemented using existing computer processors, or by a special purpose computer processor for an appropriate system, incorporated for this or another purpose, or by a hardwired system. Embodiments within the scope of the present disclosure include program products comprising machine-readable media for carrying or having machine-executable instructions or data structures stored thereon. Such machine-readable media can be any available media that can be accessed by a general purpose or special purpose computer or other machine with a processor. By way of example, such machine-readable media can include RAM, ROM, EPROM, EEPROM, CD-ROM or other optical disk storage, magnetic disk storage or other magnetic storage devices, or any other medium which can be used to carry or store desired program code in the form of machine-executable instructions or data structures and which can be accessed by a general purpose or special purpose computer or other machine with a processor. Combinations of the above are also included within the scope of machine-readable media. Machine-executable instructions include, for example, instructions and data which cause a general purpose computer, special purpose computer, or special purpose processing machines to perform a certain function or group of functions.

Although the figures may show a specific order of method steps, the order of the steps may differ from what is depicted. Also two or more steps may be performed concurrently or with partial concurrence. Such variation will depend on the software and hardware systems chosen and on designer choice. All such variations are within the scope of the disclosure. Likewise, software implementations could be accomplished with standard programming techniques with rule based logic and other logic to accomplish the various connection steps, processing steps, comparison steps and decision steps.

What is claimed is:

1. A computerized method of assigning a building automation system point type to a plurality of unclassified data points of a building automation system, the method comprising:

receiving, at a processing circuit, the plurality of unclassified data points from one or more subsystems or devices of the building automation system, each of the unclassified data points comprising at least one attribute containing a substring;

classifying each data point of a first subset of the unclassified data points by associating a building automation system point type of a plurality of building automation system point types with each data point of the first subset, wherein remaining unclassified data points form a second subset;

generating a term set containing the substrings that appear in the attributes of the first subset of data points;

calculating, for each substring in the term set, a frequency value indicating a frequency that the substring appears in the attributes of the first subset of data points associated with one of the building automation system point types;

repeating the calculating for each of the building automation system point types such that a frequency value is calculated for each unique combination of a selected substring and a selected building automation system point type;

generating a first matrix, each element of the first matrix corresponding to one of the unique combinations and containing the frequency value calculated for the unique combination;

using the elements of the first matrix to calculate, for each of the unique combinations, an indicator of a probability that the presence of the selected substring in the at least one attribute of a data point results in the data point belonging to the selected building automation system point type;

assigning a building automation system point type to each data point of the second subset by finding the substring and potential building automation system point type pair having the greatest indication of probability; and

using the data points of the second subset with the assigned building automation system point types to control one or more subsystems or devices of the building automation system.

2. The method of claim **1**, wherein generating the first matrix comprises:

collecting data points of the first subset classified as the same building automation system point type;

concatenating the attributes of the data points of the first subset classified as the same building automation system point type;

calculating, for each of the substrings, the frequency the selected substring appears in the concatenated attributes associated with each building automation system point type; and

constructing the first matrix with columns of the concatenated attributes, rows of the substrings, and individual elements of the frequency that the selected substring appears the concatenated attributes associated with the selected building automation system point type.

3. The method of claim **2**, wherein calculating the indicator of the probability comprises using a naive Bayes classifier.

4. The method of claim **3**, wherein generating the first matrix comprises using latent semantic indexing.

5. The method of claim **2**, wherein generating the first matrix further comprises weighting the frequency that the selected substring appears in the concatenated attribute associated with the selected building automation system point type using an inverse document frequency factor.

6. The method of claim **2**, wherein the indicator of the probability, for each of the substrings and for each of the building automation system point types, is equal to the frequency that the selected substring appears in the concatenated attribute associated with the selected building automation system point type summed over the substrings and the concatenated attributes associated with each building automation system point type, divided by the number of the occurrences of any of the substrings in the concatenated attributes associated with the selected building automation system point type.

7. The method of claim **2**, wherein generating the first matrix further comprises:

deconstructing the first matrix using singular value decomposition into the product of a second matrix, a third matrix, and a fourth matrix;

constructing a fifth matrix using portions of the second matrix, the third matrix, and the fourth matrix, wherein

the portions are defined by a quality control constant, and wherein the fifth matrix is an approximation of the first matrix.

8. The method of claim **7**, wherein the indicator of the probability, for each of the substrings and for each of the plurality of building automation system point types, is equal to the cosine distance of a vector describing the selected substring and a vector describing the selected building automation system point type.

9. The method of claim **1**, further comprising:

receiving a second plurality of unclassified data points and at least one attribute for each data point;

generating at least one additional term set containing substrings that appear in the attributes of the at least one additional plurality of unclassified data points;

calculating a dissimilarity indicator using the term set and the at least one additional term set; and

generating a new term set containing substrings of the first subset of data points and the second plurality of unclassified data points when the dissimilarity indicator is greater than a threshold amount.

10. The method of claim **9**, wherein the dissimilarity indicator comprises a Jaccard index.

11. A system for assigning a building automation system point type to a plurality of unclassified data points of a building automation system, the controller comprising:

a processing circuit configured to receive the plurality of unclassified data points from one or more subsystems or devices of the building automation system, each of the unclassified data points comprising at least one attribute containing a sub string;

wherein the processing circuit is further configured to classify each data point of a first subset of the unclassified data points by associating a building automation system point type of a plurality of building automation system point types with each data point of the first subset, wherein remaining unclassified data points form a second subset;

wherein the processing circuit is further configured to generate a term set containing the substrings that appear in the attributes of the first subset of data points;

wherein the processing circuit is further configured to calculate, for each substring in the term set, a frequency value indicating a frequency that the substring appears in the attributes of the first subset of data points associated with one of the building automation system point types;

wherein the processing circuit is further configured to repeat the calculation for each of the building automation system point types such that a frequency value is calculated for each unique combination of a selected substring and a selected building automation system point type;

wherein the processing circuit is further configured to generate a first matrix, each element of the first matrix corresponding to one of the unique combinations and containing the frequency value calculated for the unique combination;

wherein the processing circuit is further configured to use the elements of the first matrix to calculate, for each of the unique combinations, an indicator of a probability that the presence of the selected substring in the at least one attribute of a data point results in the data point belonging to the selected building automation system point type;

wherein the processing circuit is further configured to assign a building automation system point type to each data point of the second subset by finding the substring and potential building automation system point type pair having the greatest indication of probability; and

wherein the processing circuit is further configured to use the data points of the second subset with the assigned building automation system point types to control one or more subsystems or devices of the building automation system.

12. The system of claim **11**, wherein generating the first matrix comprises:

collecting data points of the first subset classified as the same building automation system point type;

concatenating the attributes of the data points of the first subset classified as the same building automation system point type;

calculating, for each of the substrings, the frequency the selected substring appears in the concatenated attributes associated with each building automation system point type; and

constructing the first matrix with columns of the concatenated attributes, rows of the substrings, and individual elements of the frequency that the selected substring appears the concatenated attributes associated with the selected building automation system point type.

13. The system of claim **12**, wherein calculating the indicator of the probability comprises using a naive Bayes classifier.

14. The system of claim **13**, wherein generating the first matrix comprises using latent semantic indexing.

15. The system of claim **12**, wherein generating the first matrix further comprises weighting the frequency that the selected substring appears in the concatenated attribute associated with the selected building automation system point type using an inverse document frequency factor.

16. The system of claim **12**, wherein the indicator of the probability, for each of the substrings and for each of the building automation system point types, is equal to the frequency that the selected substring appears in the concatenated attribute associated with the selected building automation system point type summed over the substrings and the concatenated attributes associated with each building automation system point type, divided by the number of the occurrences of any of the substrings in the concatenated attributes associated with the selected building automation system point type.

17. The system of claim **12**, wherein generating the first matrix further comprises:

deconstructing the first matrix using singular value decomposition into the product of a second matrix, a third matrix, and a fourth matrix;

constructing a fifth matrix using portions of the second matrix, the third matrix, and the fourth matrix, wherein the portions are defined by a quality control constant, and wherein the fifth matrix is an approximation of the first matrix.

18. The system of claim **17**, wherein the indicator of the probability, for each of the substrings and for each of the plurality of building automation system point types, is equal to the cosine distance of a vector describing the selected substring and a vector describing the selected building automation system point type.

19. The system of claim **11**, wherein the processing circuit is further configured to:

receive a second plurality of unclassified data points and at least one attribute for each data point;

generate at least one additional term set containing substrings that appear in the attributes of the at least one additional plurality of unclassified data points;

calculate a dissimilarity indicator using the term set and the at least one additional term set; and

generate a new term set containing substrings of the first subset of data points and the second plurality of unclassified data points when the dissimilarity indicator is greater than a threshold amount.

20. The system of claim **19**, wherein the dissimilarity indicator comprises a Jaccard index.

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